Feature-Optimized Machine Learning for High-Accuracy Ammunition Detection in X-Ray Security Screening

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Abstract*—This paper introduces a machine learning system that is feature-optimized to enhance the detection of concealed ammunition in X-Ray security imaging. The system integrates advanced image analysis techniques with a cascade-AdaBoost classifier and Multi-scale Block Local Binary Pattern (MB-LBP) features, which are particularly effective for object recognition and classification in complex, high-dimensional data. The combination of these algorithms ensures robust performance in identifying ammunition types even under challenging conditions, such as variations in image quality or object orientation. The system is specifically designed for the accurate identification of various types of ammunition, including 9 mm bullets for handguns, AK-47 machine gun bullets, and 12-gauge shotgun cartridges. To support the development and testing of this system, a new dataset comprising 1,732 X-Ray images of passenger luggage was collected. This dataset is made publicly available to facilitate further research and improvement in this critical area of security technology. Experimental results demonstrate that the system achieves a high level of detection accuracy, with the ability to identify 12-gauge shotgun shells concealed in baggage with a 92% success rate. Beyond its technical achievements, this system significantly enhances the efficiency and reliability of security checks, improving the overall effectiveness of ammunition detection in real-world scenarios.

***Keywords*—Feature optimization; ammunition detection; X-Ray images; machine learning; security imaging**

I. Introduction

In the 21st century, there are rapidly increasing needs in many urban-related areas due to the current growth of urban populations, including environmental governance, public safety, city planning, industry facilitation, resource utilization, energy conservation, traffic control, telemedicine, homecare, and interpersonal relationships, social interactions, entertainment, and communication. Failure to satisfy any of the criteria could threaten a city's ability to grow sustainably. Smart cities play a critical role in the advancement of humanity, which often depends on widely dispersed smart devices to monitor the urban environment in real-time, react quickly, establish automated control, gather data for intelligent decision-making, enable various services, and enhance the quality of urban living [1].

These days, fast, smooth, and efficient transport of people and their luggage has become very important in this fast-paced modern lifestyle. Much attention has also been paid recently to the security and safety of passengers by the aviation industry. Occasionally, national safety, economic structure, and infrastructure rely on a secure and safe airport system. Therefore, much time and effort are continuously being exerted in order to develop a safer policy and improve airport security. However, despite all these precautions, there are many terrible accidents that occur regularly indicating limitations and drawbacks in the currently used security systems [2].

In airports, security checkpoints use metal detectors or X-ray detection systems for discovering metallic objects along with high-tech plastics or ceramics, composite weapons, illegal drugs, explosives, ammunition, or other items that can be smuggled [3]. There are many places such as airports, public places, and sensitive buildings that use manual screening for detecting unauthorized and concealed items and weapons [4]. These systems can be very effective, quick, and dynamic, regardless of the enormous number of individuals accessing these areas. Dillingham [5] determined several constraints and challenges in the capability of the screening procedures to discover suspicious items on the body or the luggage of the passengers. Consequently, it can be concluded that the conventional manual screening processes that are still used at many airports are incapable of detecting all the concealed and threatening weapons because of the restrictions in the technology and in the performance of the personnel [6].

The baggage screening and inspection process takes a lot of effort and time. On the other hand, many passengers also complain that the screening procedures invade their privacy by scanning and checking their personal stuff and belongings [7]. Conventional security systems count totally on the performance, perceptions, judgment, and ability of the security personnel in making decisions [8]. However, it is argued that human recognition systems are more accurate and efficient than automated systems. Nevertheless, there are many additional factors, such as placing objects at unexpected angles, that prevent object discovery by using their images [9]. In the same context, the Congressional Research Service (CRS) report to congress has stated that several factors could contribute to limiting human performance such as tiredness, a lack of job satisfaction or motivation, inadequate training, and unsuitable workplace conditions, which affect their performance and even their standards of success [6]. Other studies [10][11] have stated that after working for long time periods, the human eyes get exhausted and tired. In addition, when humans have been working on the same mission for long time periods, they can get bored due to monotonous tasks and lose their interest and energy. This could lead to an erroneous reading and inexpedient analysis of the information; this would result in negligence in discovering the presence of concealed weapons or such items [2]. Moreover, a cluttered X-ray image of the passenger's belongings contains many shapes and colors [12], which could overload the security personnel and make the detection of weapons or explosive devices more difficult amongst the other personal items carried by the passenger.

Metal detection machines used for detecting metallic objects at airport security checkpoints raise an alarm for every metallic object passing through them. Even though a majority of the items are harmless, they still raise false alarms. Since many false alarms are raised every minute by these metal-detecting machines, even the security personnel find it annoying and ignore them. This practice could be responsible for many of the undetected suspicious metallic objects passing through the detectors [9]. In order to provide better security at the airports, more reliable, enhanced, and fast-screening systems are necessary for inspecting baggage at airports. This system has two objectives. First, the system must be able to analyze and study every X-ray image. Then it must contain a suspicious object detection application. A novel and automated system that carries out fast and reliable baggage monitoring must be developed. It will need less processing time and provide more accurate results. Though there are many X-ray techniques for detecting suspicious objects, there are no specific ones that focus on ammunition detection. However, there are many techniques that detect the presence of concealed weapons like knives, handguns, etc., depending on the size, shape, and the material's response to the X-ray radiation. Some of the common X-ray image-processing techniques, which are used for Concealed Weapon Detection (CWD), include image enhancement and de-noising, object segmentation, shape description, and detection and recognition of weapons [11][13][14].

In this research, for the first time, a novel dataset with 1732 X-Ray images of passenger luggage has been developed specifically for this use. The public is given access to this special dataset so that other researchers can use it. Authors propose a novel automatic system that detects different kinds of ammunition concealed in passenger baggage and carry-on items. This system can be used to enhance and support the conventional inspection techniques. Literature analysis suggested that many authors have carried out CWD techniques using image sensors, IR waves, and X-rays; however, those techniques could only detect metallic objects and were unable to detect non-metallic weapons, i.e., made of ceramics or plastics such as 12-gauge shells [7].

The content of the paper can be summarized as follows: Section II presents a literature review of detecting concealed weapons and concealed ammunition using different machine vision and image processing techniques. Section III describes the implementation of a smart system that would increase safety and security levels at airports by supporting security expert's ability of 9 mm hand-gun bullets, AK-47 machine gun bullets, and 12-gauge shotgun shells. Section IV outlines the performance of the detection evaluation with some confirmatory ranking results and analysis. Finally, Section V presents the conclusions of this paper.

II. Literature Review

In order to effectively manage data analysis, data communications, and the successful implementation of complicated policies to maintain the smooth and secure management of a smart city, the efficient use of artificial intelligence (AI) and machine learning (ML) techniques is vitally important [15]. Big data analysis and the successful application of AI and ML have increased the efficiency and scalability of smart cities [16]. In order to improve the efficiency of passenger investigation and ensure safe journeys, ML-based techniques have a significant impact on the present intelligent transportation system (ITS) [16][17].

Several researchers have utilized AI-based approaches to ensure the safety of the smart city environment [18]. Based on neural networks, the authors of [19] presented an effective crime detection system for a smart city to quickly locate and assess any criminal behavior. In the same context, the authors of [20] also suggested an ML-based architecture that might be used to anticipate incidents and provide responses before they occur. To realize future trends and the use of IoT in the intelligent transportation system, the applications employed in the IoT-based transport model are thoroughly examined in [21].

Many studies have been proposed in the literature for the purpose of detecting concealed weapons using different machine vision and image processing techniques. However, few studies have addressed the detection of concealed ammos. In the study by Kase [9], the author investigated and implemented various color-coding schemes for the detection of suspicious and threatening objects using X-ray images. The author argued that the use of these techniques would help in the detection of threatening objects and would improve the efficiency of the baggage monitoring, as well as decreasing inspection time and the possibility of fatigue-based errors.

There are several studies that have addressed the automatic detection of ammunition. These studies can be categorized according to the areas of application into six categories, which are: detection of concealed weapons such as [22], detection of unconcealed weapon [23], gun detection [24], knife detection [25], weapon detection using X-ray imaging [26], and weapon detection using infrared imaging [27]. It is worth mentioning here that some studies can be grouped in more than one of those categories.

However, the methods used for the detection of concealed ammunition can be grouped into four categories: matching based [28], classifier-based [29], multisensor-based [30], and detector-based [29]. This study proposes a classification-based approach to address concealed-munition detection using X-ray imaging.

Regarding the classifier-based approaches, weapons, ammunition, and bullets are segmented from the image, and then the region of interest (ROI) are utilized to extract features that will be used later for classification [31]. The main role of the classification approach is to classify images as positive or negative. The presence of the ammunition in the input image indicates positive and the absence of the ammunition means negative. Thus, segmentation of ROI is considered a critical phase in the classifier-based approaches to extract the required features for classification.

Several studies employed a classifier-based approach for the purpose of weapons detection and different traditional techniques were utilized in these studies to extract features from the segmented ROI [32]. These techniques include active contour shape, Fisher's linear discriminant, watershed level sets, Fuzzy connectedness, k-means algorithm, and region growing [33]. On the other hand, there are other studies that employed deep learning models as a base for the classification process. Lai et al [34] firstly presented in 2017 a deep learning approach in the field of gun detection to classify images. Their approach used the GoogleNet pre-trained model to train input images. The authors of [26][35] carried out a set of pre-trained deep learning models for classification of images that include weapons and guns. Either using the traditional techniques or deep learning techniques to extract features, both of them lead to inefficient accuracy in the detection of weapons for the small size of weapons. Moreover, most of the published studies in this domain addressed the issue of weapons detection (i.e., that have a relatively large size) but neither addressed ammunition/bullets detection nor the types of ammunition.

Sadah et al. [11] proposed a hybrid technique for improving digital X-ray images by combining the frequency domain enhancement and optimal spatial image techniques. In their method, they selected these frequency domain enhancement techniques: Gaussian and Butterworth high and low pass filters, and as for the spatial domain methods: power-law transform, Histogram equalization, and Negative transform. They carried out more than 80 probable combinations, and some combinations optimally enhanced the original X-ray images. In the study by Khan and Chai, the authors proposed an approach that combined the high and the low-energy X-ray images, denoised the images, and improved the fusion image using histogram specifications, and it also improved the contrast. Their results showed that the final image contained all the minute details; it had no background noise and had enhanced contrast. These images could be easily interpreted and automatically segmented by security personnel. This will result in decreasing the false alarm rate during the X-ray baggage inspection.

Another study carried out by Al-Najdawi [2] proposed another approach that detected different types of bullets and shotgun shells. Different image processing techniques were applied in the detection process, which includes image enhancement, conversion, labeling of connected components, and geometric distance calculations. The author built a dataset comprising 150 X-Ray images of passenger's luggage that contain different types of ammunition and proposed a wideband millimeter-wave imaging system which carried out a fast inspection of the baggage for detecting concealed weapons, explosives, handguns, etc.

Image fusion techniques combine relevant information from many images, those techniques can be classified into the spatial domain and the transform domain. The spatial domain method includes the averaging approach, principal component analysis, the Brovey method, and the Hue-Intensity-Saturation (HIS) transformation approach. The high pass filtering-based processes are also included in the spatial domain approaches [36]. On the other hand, the transform domain approaches can easily handle the spatial distortion after image fusion. In the work proposed by Xue et al. [37], the authors developed an algorithm that merged the color visual images and their corresponding infrared (IR) images for CWD. This color image fusion algorithm proved to maintain the resolution of the image and could incorporate the detected weapons in the image while maintaining the natural colors of the image. In a study by Achanta et al. [38], the authors developed a method known as parametric mixing. In their study, they created a model which improved the detection of objects (i.e., metallic or non-metallic) or concealed weapons using a nonlinear acoustic technique. In their method, ultrasonic waves were used for creating a localized zone, in which the nonlinear interaction generated a low-frequency acoustic wave that could go through the clothing in a better manner when compared to direct ultrasonic waves.

Microwaves can be used for communication, i.e., for transmitting long-distance telephone signals and in satellite television. They are also used for detecting concealed metal. Elsdon et al. [39] suggested an approach for detecting the concealed metallic objects like weapons by using an indirect holographic process, which was operational at the optical frequencies. This approach could be applied to the image objects at the microwave frequencies, and it could determine the shape and location of the concealed objects. Since the microwave imaging methods is very expensive, researchers have proposed a simple and inexpensive method of using this technique for CWD.

One of the biggest problems facing researchers in the field of ammunition identification is the lack of publicly available benchmark datasets according to [30]. As a part of the contribution in this research, a novel dataset of 1732 X-Ray images of passenger luggage has been produced especially for this purpose. This unique dataset is made available to the public so that other scholars may use it.

III. Feature-Optimized Approach for Ammunition Detection

A. Feature Selection Techniques

The proposed system for the detection of ammunition from X-ray images would be as effective as the features that are extracted from the images. Due to the complexity of the images and the necessity to distinguish between the hidden ammunition, feature selection was an important step in the model training and improving its performance. In this study, the MB-LBP features were chosen based on their efficiency in describing the micro and macro-structures that are seen in the X-ray images. These features are especially useful for the identification of separate bulk density and shape of different types of ammunition. In the feature selection, the numerous possibilities of features such as texture descriptors, the shape-based features, and the intensity gradients were considered. By cross-validation, only the useful features were kept in the model. To do so, we sought to maximize the distinction between the selected features while reducing overlapping as much as possible to include only the most important features for the classification process. This was an iterative process in which features had to be assessed not only by their ability to separate classes but also as components of a set of features that defines the model. The purpose was to achieve high accuracy to guarantee that the final set of the features is both as small as possible and as accurate as possible.

The selected features were also chosen for their insensitivity to variations in conditions typical for real-world security scenarios, light conditions, object orientation, occlusions in X-ray images, etc. Thus, it was ensured that the set of features being used was rather stable with regards to these changes and by using this set of features, the system was made more robust to changes in the environment and situations. However, the focus was also paid to the interpretability of the chosen characteristics that were used for the definition of the described model. This was important so that actions of the system could be explained and be accepted by security personnel. For example, the features of the MB-LBP include clear and interpretable representations of the visual data on which the system makes its classification, which facilitates an understanding of the process that led to the classification. This transparency is important for practical implementation in serious security scenarios where not only the decision but the rationale for the decision may be critical for use. This concentration on feature selection not only enhanced the model's accuracy but also developed confidence that the system could work in real-time, making it an important tool in supporting security in areas like airports and essential installations.

B. Ammunition Detection: 9 mm Handgun and AK-47 Bullets

The greyscale images are produced by measuring the light intensities at every pixel in the band of an electromagnetic spectrum (e.g., IR, X-ray, visible light, or UV). Under these circumstances, they are monochromatic only when a light frequency is captured; however, they can also be synthesized using colored images. Grey X-rays images are an old and popular method for carrying out security checks. During baggage inspection, the luggage is exposed to small ionizing radiation doses, which results in images of the luggage's interiors [40]. However, digital X-ray images can be degraded due to low contrast and blurring, which is caused by the complex items in the luggage. Also, scattering of the X-rays and electrical noises can affect the monitoring and the analysis of the images by some systems or humans. Hence, it becomes necessary to improve the X-ray image details in order to improve the visual quality of the images [41]. Ammunition is smaller in size as compared to the other personal items in the luggage; hence, the X-ray images must be improved as in the following step.

1) X-ray image enhancement: Methods of enhancing the X-ray images within a spatial domain can be divided into three groups: point processing techniques, histogram-based processing techniques, and mask processing techniques [42]. In this study, the authors have used the histogram equalization and the unsharp masking techniques. Histogram equalization is a contrast enhancement process, which adjusts the pixel intensities for generating a new and enhanced image that shows a better local contrast. On the other hand, the unsharp masking technique sharpens the images by subtracting the smoothed image from the original image. A histogram can be created for an image based on the probability of the occurrence of the pixel intensity as described earlier [43]:

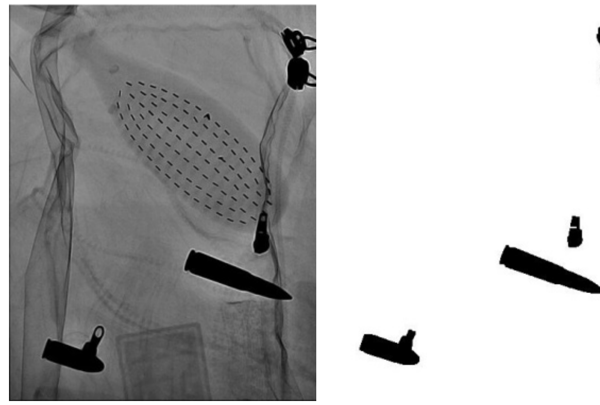

Fig. 1. Samples of the X-ray images of: (a) 9 mm handgun bullets and AK-47 machine gun bullets; (b) Resultant binary image.

$$P_r(r_k) = \frac{n_k}{MN} \tag{1}$$

Where $P_r(r_k)$ refers to the probability of the occurrence of the intensity level r_k within a digital image, MN refers to the total pixels within an image, and n_k represents the number of the pixels with an intensity r_k. New intensity values can be estimated for every intensity level using the transformation as follows:

$$s_k = T(r_k) = (L-1)\sum_{j=0}^{k} p_r(r_j) \tag{2}$$

Where s_k refers to the new intensity level. It is estimated for every pixel in an image. In addition, the processed image can be obtained after mapping every pixel in an input image (having intensity r_k) into the corresponding pixels (with intensity level s_k) into the output images [23]. The unsharp masking procedure is carried out after blurring the original images and then creating the mask after subtracting the blurred images from the primary images as follows:

$$W_{mask}(x,y) = f(x,y) - f'(x,y) \tag{3}$$

Where $W_{mask}(x,y)$ is the mask, $f(x,y)$ represents the primary image, and $f'(x,y)$ refers to the blurred image. Thereafter, the mask is added to the primary image as follows:

$$W(x,y) = f(x,y) + W_{mask}(x,y) \tag{4}$$

Where $W(x,y)$ refers to the resultant unsharp image.

2) Ammunition detection: Ammunition detection is initiated by converting enhanced images into binary images with the help of the Otsu threshold process [43]. The images are denoised using some morphological operators. Then, the objects connected at the borders are eliminated from the resultant binary images. Finally, certain holes in the images are removed by morphological operators [43]. The Otsu threshold process searches for the threshold that decreases the intra-class variance, which can be defined as the weighted sum of the variances of the two classes:

$$\sigma_w^2(t) = w_1(t)\sigma_1^2(t) + w_2(t)\sigma_2^2(t) \quad (5)$$

Where the weights w_i refer to the probabilities of the classes, which are divided by the threshold t, and σ_i^2 refer to the variances of the class. Fig. 1 describes the final binary images after techniques like histogram equalization, unsharp masking, and the Otsu's thresholding method were applied to the X-ray images.

For the ammunition detection and classification, the connected regions in the binary images can be determined with the help of the connected-component labeling algorithm [44]. Here, the authors have applied the 8-connected component labeling algorithm. In the case of the binary image, the connected pixel areas can be classified after the connected component labeling operator has scanned the image in every row till it reaches a point p (where p represents the pixel labeled at any step during scanning). After recognizing this condition, the algorithm investigates the 4 neighbors of the point p, which were already scanned. The point p is labeled based on the collected data as shown below [29]:

- If all the neighboring points are 0, a new label is allocated to p.
- An exclusive label is allocated to every class with the help of the Floyd-Warshall algorithm.
- The image is scanned again, and every label gets replaced by the label that is allocated to the equivalence classes.

Fig. 2. Some samples of the X-ray images after ammunition detection: First row, 9 mm handgun bullets, AK-47 Machine gun bullets, and the 12-Gauge shotgun shells. Second row, resultant binary images.

In the next step, the properties of each connected component are estimated. Here, the authors have measured the properties for every labeled region of the label matrix. The positive integer elements present in the label matrix are seen to correspond to other areas. For example, the elements in the label matrix equivalent to 0 correspond to region 1, while the elements in the label matrix equivalent to 1 correspond to the region 2. Every labeled connected component gets indicated by a bounding box as described in Fig. 2. In order to determine if the bounding box contained ammunition images, a classification system was introduced. In this study, for testing purposes, the authors classified the ammunition in three classes: AK-47 machine gun bullets, 9-mm handgun bullets, and 12-gauge shotgun ammunition.

In the case of the AK-47 machine gun bullets and the 9-mm handgun bullets, the ammunition is classified based on their fixed bullet size ratio (i.e., length: width). In Table I, the dimensions and ratio of the bullets are summarized.

TABLE I. DIFFERENT DIMENSIONS AND RATIOS OF THE SELECTED AMMUNITION FOR TESTING OF THE DEVELOPED SYSTEM

Dimension and Ratio	9mm	AK-47	12-Gauge
Length (range)	2.781-2.969	5.600-5.620	5.1-7.6
Width	1.01	1.135	13.41
Ratio	2.75-2.93	4.93-4.95	3.80-5.66

For determining the bullet ratio in Table I, every label is estimated with the help of the Euclidean distance measure D_e for the points p and q that are located at the coordinates of (x, y) and (s, t), respectively, as:

$$D_e = \sqrt{(x-s)^2 + (y-t)^2} \quad (6)$$

Euclidean distances are used for measuring the height D_{e1} and the width D_{e2} of every object in the label, while the height:width is estimated as $R = D_{e1}/D_{e2}$. Thereafter, this ratio is compared to the results in Table I, after which the object is classified. Fig. 2 describes some samples in which the algorithm could accurately identify 9 mm handgun and AK-47 machine gun bullets, with precision 95%. Fig. 3 shows some sample images of the detected ammunition.

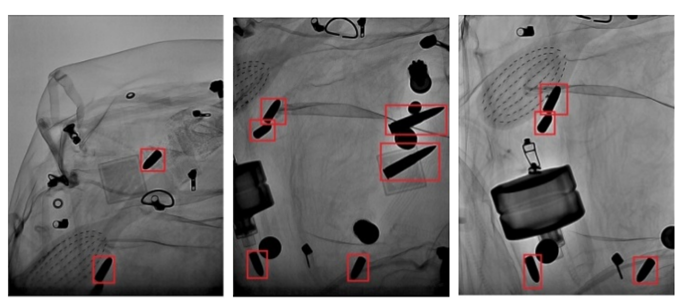

Fig. 3. Some sample images of the detected ammunition.

C. Feature-Based Identification of 12-Gauge Shotgun Shells

In this research, the authors attempt to identify the 12-gauge shells, as their structure differs from other kinds of ammunition such as the 9-mm handgun and the AK-47 machine gun bullets. The 12-gauge bullets have a plastic casing; hence, the bullets appear transparent in X-ray images. Moreover, as shown in Fig. 4, the wad creates a space between the powder and shot which prevents its visual recognition. Therefore, any orientation change in the 12-gauge position results in different shapes, as shown in Fig. 5. On the contrary, other bullets have a solid metal body, which can be identified in the X-ray images as a solid known structure.

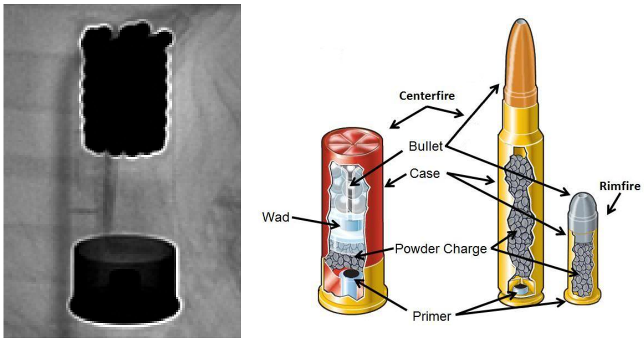

Fig. 4. (a) Structure of the 12-gauge ammunition, AK-47 machine gun bullet, and 9-mm bullet. (b) X-ray images of the 12-gauge ammunition.

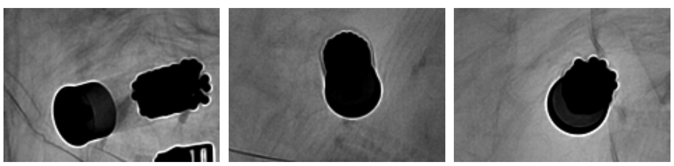

Fig. 5. Images of the 12-gauge ammunition from various angles. Image courtesy: Al-Najdawi and Tedmori.

In this study, a Cascade-AdaBoost classifier with MB-LBP features has been implemented for detecting the variable 12-gauge ammunition shapes.

AdaBoost classifier, proposed by Freund and Schapire [45][46], is a type of parallel classifier that combines various linear weak classifiers. This offline classifier self-adaptively increases the number of weak classifiers, which helps improve the overall classification accuracy. Every weak classifier is seen to focus on the 1-D classification of the input feature vectors. Moreover, the AdaBoost algorithm makes use of a minimal error for estimating the weight value of the weak classifier, then it uses the weight value of each training sample input. Then, it passes the weight value to the newly added subsequent weak classifier. Fig. 6 describes the AdaBoost classifier architecture [47].

If the input feature vector is represented by f, then the number of the weak classifiers is represented by $h_t(f)$, $t = 1, \ldots, T$, and the corresponding weight values of every weak classifier are represented by β_t, $t = 1, \ldots, T$. The final strong classifier, $H(f)$, can be expressed as follows:

$$H(F) = \text{sign}\left\{\sum_{t=1}^{T} \beta_t h_t(f)\right\} \tag{7}$$

One main limitation of the AdaBoost classifier is that it has a higher false alarm rate. Thus, Viola and Jones [48] proposed the cascade-AdaBoost classifier to decrease the false alarm rate. Fig. 7 shows the architecture of the cascade-AdaBoost classifier, where every classifier was an AdaBoost classifier.

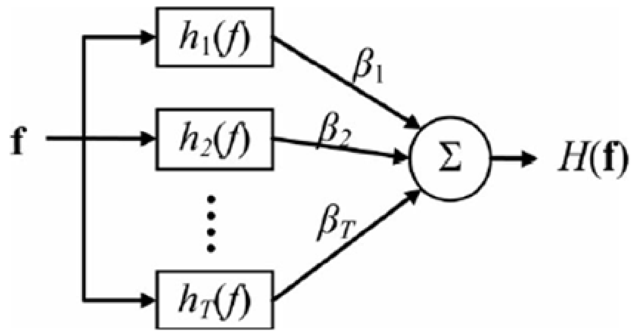

Fig. 6. Architecture of the AdaBoost classifier [47].

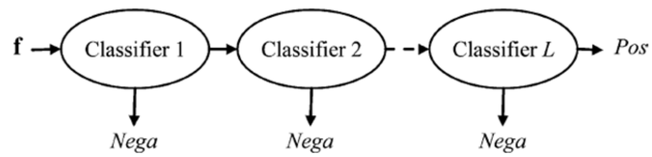

Fig. 7. Cascade-AdaBoost classifier architecture [48].

When the input feature vector is passed through the first AdaBoost classifier and is determined as the negative example, it is removed from the training set before it enters the second AdaBoost classifier. This decreases the number of the examples and increases the layers for removing the negative examples. However, when passing the input feature vector through the first AdaBoost classifier, if it is identified as a positive example, then the training example enters the second layer of the AdaBoost classifier and is classified further until it passes to the last layer. Hence, the cascade AdaBoost classifier displays a high detection rate and a lower false alarm rate since it uses many classifiers [49].

AdaBoost learning is applied for the selection of some weak classifiers and then combines them into the classifier to determine if the image contains the desired object [50]. Several algorithms can be used for feature extraction, like the Principal Component Analysis (PCA) [51], the Linear Discriminant Analysis (LDA) [52], the Independent Component Analysis (ICA) [53], and the Gabor filter [54]. However, all of these algorithms have high computational costs for convolving the object images and can be inefficient with regard to memory and time to extract features compared to the Local Binary Pattern (LBP) [55]. The LBP method was initially proposed by Ojala et al [56], and it was used for the texture description. This method can be used for many applications, such as facial detection and recognition [57][58], classification of gender and age [59][60], analyzing facial expressions [61], and estimating the head pose [62]. Some main properties of the LBP features

IV. Discussion and Experimental Results

A. Comparative Analysis of Feature Selection Techniques

The reasons for choosing the MB-LBP features in the study are based on the performance of these features in capturing the required level of details that are crucial for the identification of ammunition in X-ray images. That is why, although there are many other techniques such as Gabor filters, Histogram of Oriented Gradients (HOG) and so on, or traditional Local Binary Patterns (LBP), in this work, the MB-LBP was chosen because of the high accuracy in combination with acceptable computational time.

Some of them, such as the Gabor filters, are particularly efficient in texture analysis and have been applied in a large variety of image processing applications. However, their computational complexity is a major disadvantage in real-time environments, especially when analyzing high-dimensional data such as X-ray images. Likewise, the HOG features are very good for edge and gradient information and are used for object detection; however, they may not be as effective in discriminating between small and closely grouped objects such as ammunition.

Although traditional LBP is faster in computation and requires fewer parameters, it focuses only on the local binary patterns without regard to the spatial relation around the center pixel, which may cause a problem in complex scenes where objects are overlapping or images have different quality. The MB-LBP approach improves upon the standard LBP approach by including larger patterns, better suited to handle the difficulties posed by X-ray imagery in security systems.

Consequently, the features of the MB-LBP were chosen for this study because of their ability to give more detailed descriptions of the X-ray images in addition to capturing more global characteristics of the images. This is in concordance with the characteristics of the ammunition detection task where precision and speed are critical. Another reason for our choice of MB-LBP was based on the observation that it has been widely used in similar applications and is generally robust for different conditions.

Comparing MB-LBP directly with other techniques was beyond the scope of this study. However, the literature shows that MB-LBP is suitable for the present task. This feature selection method is also balanced in terms of the performance and computation, and that is why its application in developing a real-time detection system in the security sector is advisable.

B. Experimental Results

In the experiments provided in this research, positive and negative samples were required in the training procedure. Positive samples (548 images that contain more than 1036 of 12-gauge ammunition) were obtained through labeling the 12-gauge ammunition from the X-ray images. Negative samples (1184 images) were extracted from X-ray images which do not contain the 12-gauge ammunition. The X-ray images of the 12-gauge ammunition that have been used in the experiments were taken from various view angles as shown previously in Fig. 5.

In the following experiments, an eighteen-layer cascade-AdaBoost classifier using MB-LBP features is obtained and then experimented over the provided dataset (i.e., offline process). Then a real-time process starts depending on the previous features which have been obtained from the MB-LBP to classify the required objects. Using this framework, it was able to process more than 27 frames per second on a machine of 8 GB RAM and 3.2 GHz processor speed. Sample of the results are shown in Fig. 8.

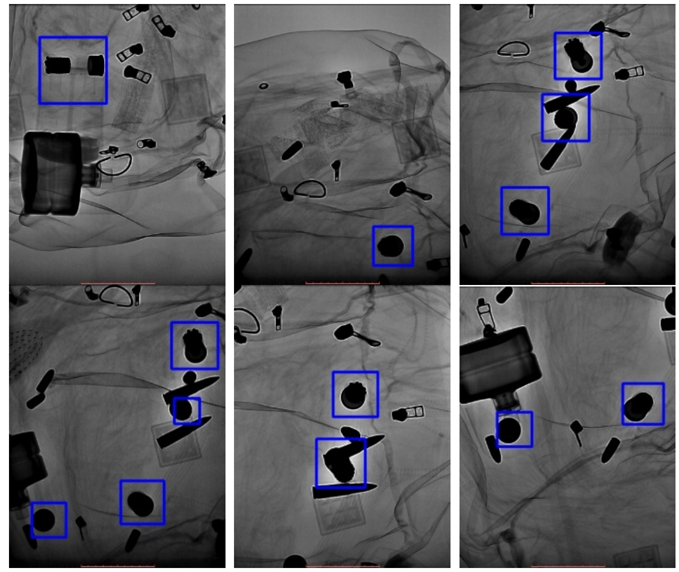

Fig. 8. Sample of successful labeling for different numbers of 12-gauge ammunition of different orientations.

However, in some cases, the proposed system failed to label the 12-gauge ammunition correctly by selecting different objects that contain similar features to the 12-gauge ammunition, as shown in Fig. 9.

In order to evaluate the performance of the proposed system, some statistical measures (i.e., accuracy, sensitivity, specificity, and Matthew's correlation coefficient) were calculated as follows:

- Accuracy has been calculated for the 12-gauge ammunition detection using the formula [63]:

$$\text{Accuracy} = \frac{\Sigma\ (TP + TN)}{\Sigma\ (TP + TN + FP + FN)} \times 100\% \tag{8}$$

  Where:
  - TP = True Positive (actual 12-gauge ammunitions that were correctly classified as 12-gauge ammunitions).
  - FP = False Positive (other objects that were incorrectly labeled as 12-gauge ammunitions).
  - FN = False Negative (12-gauge ammunitions that were incorrectly not labeled).
  - TN = True Negative (all the remaining objects, correctly classified as non-12-gauge ammunitions).

  In the proposed system, Accuracy = 92.8%, where: TP = 960, TN = 1151, FP = 88, and FN = 76.

- Sensitivity or true positive rate (TPR) relates to the ability to identify positive results using the formula [63]:

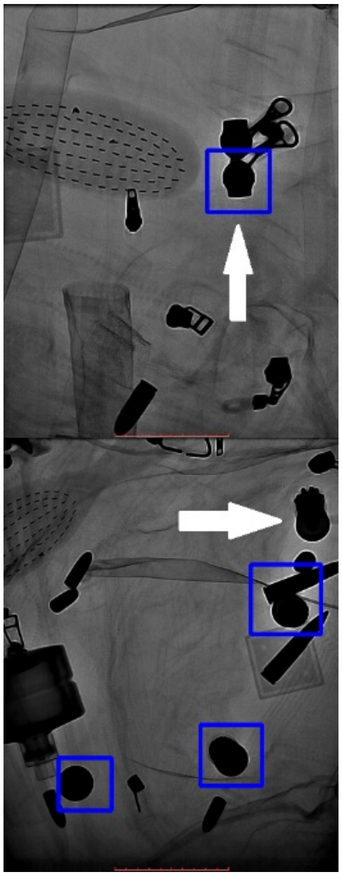

Fig. 9. Some of the cases where the system was unable to label the 12-gauge ammunition were in (a) labeling a different object or (b) missing the object completely.

$$\text{TPR} = \frac{TP}{TP + FN} \times 100\% \quad (9)$$

TPR = 92.66%, where: TP = 960 and FN = 76.

- Specificity (SPC) or true negative rate relates to the ability to identify negative results using the formula [63]:

$$\text{SPC} = \frac{TN}{TN + FP} \times 100\% \quad (10)$$

SPC = 92.89%, where: TN = 1151 and FP = 88.

- Matthew's Correlation Coefficient (MCC) was used in the machine learning for measuring the quality of the binary (2-class) classification [63]. This method considered the true and the false positives or negatives and was considered the balanced measure that could be used for the differently sized classes. MCC was used as a correlation coefficient for the observed and the predicted classification systems and generated values ranging between +1 to -1. A coefficient value of +1 showed a perfect prediction, while a value of 0 indicated a random prediction, and a value of -1 indicated a complete disagreement between the observed and predicted values. MCC is directly estimated using the confusion matrix, as follows:

$$\text{MCC} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (11)$$

MCC = 85.5%, where: TP = 960, TN = 1151, FP = 88, and FN = 76.

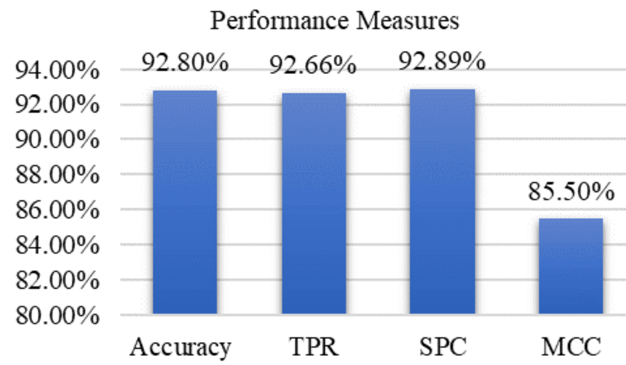

Fig. 10. Graphical representation for the performance measures (i.e., Accuracy, TPR, SPC, and MCC).

Different applications could benefit from the results of this research by applying the MB-LBP offline process as in [36][37]. Fig. 10 shows graphical representation for the performance measures (i.e., Accuracy, TPR, SPC, and MCC).

C. Comparative Analysis

In this part we compare our results with those of the related paper, "Detection of threat objects in baggage inspection with X-ray images using deep learning" by Saavedra et al. [64]. Both studies, however, address threat detection in X-ray images, and their methodologies and performances differ from each other. For this, Saavedra et al used deep learning models like YOLOv3, SSD, and RetinaNet trained on real as well as synthetic X-ray images artificially generated by PGGAN and superimposition methods. Across all four threat categories (guns, knives, razor blades, and shuriken), mAP was 80.0%. Instead, our system includes a cascade-AdaBoost classifier using the accuracy of the Multi scale Block Local Binary Pattern (MB-LBP), and is tuned for ammunition detection. The methodology described results in a 92.8% accuracy detecting 12-gauge shotgun shells, 92.66% sensitivity and 92.89% specificity.

However, guns and shuriken had high precision (96.3%, 93.7%) according to Saavedra et al. but knives with elongated shape and occlusion problems achieved low precision (76.2%). However, our system retains strong performance in detecting 12-gauge shotgun shells, which are very difficult to detect since the shells are covered in plastic casing and have multiple orientations. Cascade-AdaBoost classifier with MB-LBP features are capable of overcoming these challenges, reaching 92.8% accuracy and 85.5% MCC. In a particular dataset with similar threat objects to the training set, Saavedra et al. used their model and achieved high precision. But their model was not able to account for significantly different objects from what they trained from. Table II shows comparative analysis of

TABLE II. COMPARATIVE ANALYSIS: FEATURE-OPTIMIZED MACHINE LEARNING SYSTEM VS. DEEP LEARNING-BASED THREAT DETECTION

Aspect	Our System (Feature-Optimized ML)	Saavedra et al. (Deep Learning-Based)
Methodology	Cascade-AdaBoost classifier with Multi-scale Block Local Binary Pattern (MB-LBP) features.	Deep learning models (YOLOv3, SSD, RetinaNet) trained on real and synthetic X-ray images (PGGAN).
Dataset	1,732 X-ray images of passenger luggage with concealed ammunition (publicly available).	GDXray dataset with simulated X-ray images (real and synthetic).
Threat Objects Detected	9 mm handgun bullets, AK-47 machine gun bullets, 12-gauge shotgun shells.	Guns, knives, razor blades, shuriken (ninja stars).
Performance Metrics	Accuracy: 92.8% (12-gauge shells), Sensitivity: 92.66%, Specificity: 92.89%, and MCC: 85.5%.	mAP: 80.0%, Guns: 96.3%, Knives: 76.2%, Razor blades: 86.9%, and Shuriken: 93.7%.
Strengths	High accuracy for 12-gauge shotgun shells. And, robust to variations in orientation and occlusion.	High precision for guns and shuriken. And, scalable to multiple threat categories.
Challenges	Misclassification of objects with similar textures. And, reliance on single-view X-ray images.	Struggles with elongated objects (e.g., knives). And, limited generalization to unseen object shapes.
Generalization	Strong generalization to diverse orientations of 12-gauge shells. And, adaptable to real-world scenarios.	Limited generalization to objects with different shapes or orientations.
Real-World Applications	Suitable for airport baggage screening. And, reduces reliance on human operators.	Effective for detecting large threat objects (e.g., guns, shuriken).
Future Work	Integration of multi-view imaging. And, combining with deep learning models (e.g., YOLOv3).	Improving detection of small or occluded objects (e.g., knives).

feature-optimized machine learning system and deep learning-based threat detection.

In addition, we have shown here that our system can accurately identify 12-gauge shotgun shells; however, objects with similar appearances (in this case, plastic casings) were sometimes wrongly identified as ammunition. This is the problem of separating two closely related objects in cluttered X-ray images. Using the fixed bullet size ratio for classification, the system had 95% accuracy for 9 mm handgun bullets and AK 47 machine gun bullets. The elongated shape of knives typical of this type of objects, though, remains a challenge and future work may involve multi-view approaches to increase detection accuracy of such objects. The system is able to detect 12-gauge shotgun shells in various orientations and successfully detected 12-gauge shotgun shells in Fig. 8. Fig. 9 shows failed cases of the system in labeling of ammunition, primarily because of the presence of overlapping objects or similar texturing. They are valuable cases for advancing improvements, e.g., adding extra features or more refined segmentation. Due to the variable orientation and plastic casing of 12-gauge shells, the system does not perform as well with 12-gauge shells compared to 9-mm and AK-47 bullets, which are all about the same size and shape.

We show that our system is very robust to variations of the object orientation, occlusion, and image quality, and we also experimentally demonstrate that our system also facilitates the acquisition of stereo images of patients with imperfect eyes. In addition to capturing both micro and macro structures in an X-ray image, the MB-LBP has the capacity of reliable detection in complex scenarios. However, Saavedra et al.'s model did not perform well with objects when they were rotated or occluded, such as knives. This points out the importance of feature selection and necessity of models for dealing with diverse object orientations.

Our system works with high accuracy and robustness and thus is suited for security applications in real-world situations, e.g. for airport baggage screening. Security checks are significantly more efficient and reliable due to the increase in the ability to detect 12-gauge shotgun shells with an accuracy of 92.8%. Future work may also test our system with multi-view X-ray imaging, as suggested by Saavedra et al., to further improve these object detection accuracies when knives and shuriken are used.

One major shortcoming of our system is that it relies on single-view X-ray images, which might cause object that has complex shape or is under heavy occlusion to be missed. This limitation will be addressed in the future work through multi-view approaches. Further, objects with similar texture or shape are misclassified from time to time as ammunition. It is quite possible to mitigate this problem by incorporating advanced segmentation techniques or additional features. Applications in the future include adding multi-view X-ray imaging to provide a more global description of objects and enhancement of detection accuracy for hard cases. Further performance improvement is possible by combining our feature-optimized approach with deep learning models like YOLOv3 or RetinaNet because they are powerful models that are more efficient in classifying small or occluded objects. The generalization capability of the system could be enhanced if the dataset were expanded to include a greater variety of ammunition types and challenging scenarios.

V. CONCLUSION

Feature selection is a critical element in the improvement of the performance of machine learning systems, especially in tasks such as the detection of ammunition in X-ray security imaging systems. In this study, the choice and tuning of the features were critical in constructing a reliable system that can effectively detect concealed ammunition with a high level of accuracy. The features of MB-LBP were used and combined with the cascade-AdaBoost classifier in order to extract the most important information from the X-ray images and guarantee that the system can work in real-time environments. Safety and security of passengers is one of the important components of contemporary transport systems. Measures of security are tight, but threats and contraband are a reality in sensitive environments. X-ray machine systems at security checkpoints are very important in detecting banned items such as weapons and sharp objects. These systems may contain at least semi-automatic elements for metal detection. However, there is a significant gap in their capability of identifying concealed ammunition, which is a critical security threat. In an attempt to fill this research gap, this paper presents an automatic system designed to help security professionals detect different types of ammunition.

The main focus of the system is a profound feature selection method that enhances the accuracy and efficiency of the detection phase. The selection of MB-LBP features was especially useful in obtaining the fine detail required to differentiate between the types of ammunition with clarity, including 9 mm handgun bullets, AK-47 machine gun bullets, and 12-gauge shotgun shells. This feature optimization, in addition to improving the performance of the model, also decreases the system's computational intensity, making the system appropriate for real-time security applications. The authors have created their own dataset of 1,732 X-ray images of passengers' belongings that contain concealed ammunition. This dataset, now open to the public, promotes more research and development and brings together the security and machine learning domains. Thus, in addition to meeting the need for a reliable resource to support security specialists' work, the study helps to progress science and technology in the field of automated threat detection.

The system uses a number of sophisticated image processing techniques such as image enhancement, image conversion, labeling of components, and estimation of geometric dimensions. These techniques are very essential since they help to overcome the problem of variability of the X-ray image quality, orientation of objects, and the various complex backgrounds that may be observed in the passenger's luggage. The integration of the cascade-AdaBoost classifier with the MB-LBP features makes it possible for the system to perform effective and accurate detection of concealed ammunition. The combination of these mentioned methods leads to an overall effective, efficient, and flexible solution that can be implemented into different security scenarios.

In classification and recognition of concealed ammunition, the system performs quite well, especially for the 9 mm handgun bullets and the AK-47 machine gun bullets, with at most 92% accuracy in detection. Such a high level of accuracy shows how the system can greatly advance the detection abilities at the security checkpoints, with little reliance on human operators and the likelihood of human errors. The capacity to accurately identify ammunition and to do so without human intervention increases the likelihood of safety and security for passengers, especially within areas of vulnerability such as airports and other stations. Besides the efficiency, the system's architecture focuses on scalability and interpretability, which means that the developed system can be implemented in different real-world settings. It can be integrated into other security systems and structures, and it is relatively easy to modify the architecture as new threats appear on the scene. Furthermore, the system is very interpretable, and this means that security personnel can trust the decisions made by the system, which is very important when the system is being implemented in important settings.

This paper demonstrates that, in today's security systems, it is possible to enhance the performance of advanced feature selection and machine learning techniques. By focusing on the particular case of concealed ammunition searching, the authors have presented a useful instrument that could help to enhance public security and develop existing security technologies. Future work may look at applying such a scheme to identify other forms of prohibited items, as well as incorporating it within larger security systems as a way of expanding, generalizing, and ultimately increasing the practical applicability and effectiveness of the method.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The X-Ray images data used to support the findings of this study have been deposited in the Automatic-Ammo-Detection- repository (https://github.com/reyalat-bau/Automatic-Ammo-Detection-).

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